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Abstract

Electricity production from renewable sources generally displaces thermal generation, which leads to lower CO2 emissions in the power sector. However, the intermittent nature of many renewable technologies leads to greater inefficiencies in the operation of existing fossil power plants. This inefficiency translates into higher production costs as well as a higher rate of emissions relative to output. In this paper we focus on Italian power installations. Using panel econometrics, we show that a 10% increase in photovoltaics and wind infeed has reduced yearly CO2 emissions of the average thermal installation by about 4% while the average plants emissions relative to its output have increased by about 0.3% between 2005 and 2014. Given the additional inefficiency caused by intermittent renewables, our results suggest that the average installation actually only achieves around 94% of the expected reductions. The effect is more pronounced for installations that have not been retrofitted and for installations serving peak demand.

Keywords

Emission factors, load-cycling, inefficiency

1 Introduction[1]

In the past decade, there has been considerable growth in the production of electricity from renewable energy sources, in particular from solar photovoltaic (PV) and wind. For the most part, this growth has been supported by dedicated environmental and energy policies, which have impacted many power markets around the world.

Electricity production from renewable sources affects power systems in various ways. The determining factor of all those changes is that renewables have an almost zero marginal cost of production and therefore displace conventional generators with a positive marginal cost. This displacement of thermal production generally translates into lower average spot market prices (see, e.g., Green and Vasilakos, 2010; Woo et al., 2011; Würzburg et al., 2013; Paraschiv et al., 2014; Clò et al., 2015) and also impacts spot price variance (see, e.g., Wozabal et al., 2015).[2] From an environmental perspective, electricity generation from renewable sources generally leads to fewer emissions in the power sector (see, e.g., Berghmans et al., 2014, for the case of European thermal plants). This first-order effect of renewables on emissions is one of the main justifications to support the deployment of renewables in the power sector, which is the largest emitter in terms of global CO_2 emissions.[3]

The exact effect of renewables on emissions is highly heterogeneous in various dimensions: (i) spatial, i.e., across markets depending on the generation mix and therefore on the marginal plants affected; (ii) temporal, i.e., their effect differs across time respective of electricity demand (see, e.g., Novan, 2015; Graff Zivin et al., 2014; Cullen, 2013; Kaffine et al., 2013; Siler-Evans et al., 2012); and (iii) within markets depending on the installed capacity (see, e.g., Novan, 2015). In fact, the larger the amount of installed capacity, the more it affects plants at the bottom of the merit order stack, which tend to be the dirtiest and least flexible ones, i.e., coal plants.

[1]We want to thank REF-E for supporting this project by providing us their ELFO++ database. Within REF-E, we particularly thank Giulia Ardito, Donatella Bobbio, Virginia Canazza, Ana Georgieva, Giorgio Perico, and Alan Ben Seralvo for inspiring discussions. Furthermore, we want to express our thanks to Massimo Filippini, Klaus Gugler, Junsoo Lee, Xavier Labandeira, David K. Levine, Mario Liebensteiner, Alicia Pérez-Alonso, Ulrich Wagner, Elena Verdolini, Franz Wirl, and David Wozabal for their stimulating contributions and valuable suggestions to the draft version of this paper.

[2]The effect on final consumer prices, which very often includes the cost of renewable subsidies, is unclear; e.g., Cludius et al. (2014) point to the re-distributional effects between different consumer groups in Germany: industrial consumers benefit from lower average spot market prices while households and small and medium size enterprises carry most of the cost of subsidizing renewables.

[3]According to IEA Statistics (2014) electricity and heat generation accounted for 42% of global CO_2 emissions in 2012.

Many types of renewable sources – such as PV and wind – are intermittent, i.e., their power generation profile fluctuates and is partially unpredictable. This intermittency results in increased load-cycling activity of thermal units since electricity demand has to match supply instantaneously. This is especially relevant, if storage technologies, interconnection, or demand side flexibility are absent, as the only option to match demand and supply is to intensively ramp thermal units up and down, which consequently leads to higher emissions relative to output. Furthermore, operating a power generator at part-load is only possible at a reduced efficiency level. Those factors partially offset the reduction of CO_2 emissions due to the reduction in the use of fossil fuels, and also increase the cost of generating electricity. As a result, the emission factors of thermal plants, i.e., emissions relative to output, is increased. The goal of this paper is to study empirically the impact of PV and wind on the emission factors of thermal generation, in particular of coal and gas power plants.

Katzenstein and Apt (2009) were among the first to explicitly take load-cycling as a consequence to increased penetration from PV and wind into account. They use production and emission data from two types of natural gas generators and compare the actual emission offsets from PV and wind with those implied when using average emission factors. Consequently, they find that through renewable penetration, CO_2 emissions may be 20% higher than expected if the power fluctuations caused no additional emissions. Katzenstein and Apt (2009), however, measure this effect from an engineering standpoint for two gas generators only, and thus their findings lack a system perspective where the externalities of renewable generation may be shared among many power installations (Cullen, 2013).

To study the effect of renewables on emissions in market environments, recent literature has either used system-wide emissions (see, e.g., Novan, 2015; Kaffine et al., 2013, who evaluate the effect of wind generation on emissions in the Texan market), or has calculated CO_2 emissions based on average plant emission rates (see, e.g., Cullen, 2013). They all find that, on average, a MWh[4] of wind offsets between 0.5 and 0.7 tons of CO_2 emissions in Texas. We complement this literature by using data on measured emissions over time for each power installation in the Italian market while previous papers combine generation data with average plant emission factors, or estimated the impact of renewables on total market emissions. Hence, we are able to quantify the inefficiencies caused by renewables for a set of fossil fuel-fired power installations oper-

[4]MWh is a unit of energy equivalent to 1 megawatt (MW) of power expended for one hour. 1,000 MW equals 1 gigawatt (GW).

ating in a market environment rather than for two generators only, as in Katzenstein and Apt (2009).

In this paper, we study the effect of intermittent renewables, i.e., generation from PV and wind on emission factors. We apply panel data econometrics to Italian market data in the period from 2005 to 2014. Combining hourly electricity production data for 93 thermal installations with their annual CO_2 emissions, we are able to analyze the effect of additional renewable infeed on annual emission factors. To the best of our knowledge, we are the first to study the emission efficiency of thermal generation with measured emissions on installation level in a market environment over ten years.

Our results suggest that additional penetration from wind and PV positively affects the emission factor. Hence, there is an increase in emissions relative to output for the average installation. The results are significant and stable across several model specifications. Furthermore, we find that additional intermittent renewables lessens the expected reduction of emissions by about 6% for the average installation. This number is lower than in Katzenstein and Apt (2009) and highlights the importance of a system perspective where the burden of intermittency may be shared among many power installations. The time span of our sample also allows us to analyze the role of investment in more modern plants. We find a more pronounced effect for plants which have not been retrofitted. Italy's power generating system is dominated by fossil fuels but has faced considerable penetration from PV and wind over the past few years. Such transformations are currently observed in many other power systems around the world, which make our results globally relevant.

We organize the remainder of the paper as follows. In Section 2, we describe our empirical strategy to identify the effect of renewables on emission factors. Thereafter, in Section 3, we detail the data gathering and matching process. Furthermore, we briefly describe the Italian electricity market as well as the European Emissions Trading System (EU ETS). In Section 4, we present our results, quantify the increased inefficiency, and provide several robustness checks. We conclude the paper in Section 5.

2 Empirical strategy

In this paper, we apply several specifications of panel data models to pin down the effect of additional renewables in the system on emissions of thermal plants. Due to the low marginal cost of production of many renewables, it is obvious that more costly thermal generation will be offset if there is an increase in the amount of renewables in the system. This is known as the first-order effect of renewables on thermal production and henceforth on CO_2 emission reduction. However, the intermittent nature of many renewable power production sources as, e.g., wind or PV, requires thermal plants to adjust their production more frequently than in a system where only demand is variable. Thus, the second-order effect of renewables on emissions is the increased inefficiency of thermal plants induced by load-cycling. A major contribution of this paper is to quantify the magnitude of the second-order effect. Therefore, we analyze the effect of additional intermittent renewable production on the emission factors of thermal plants, i.e., their emissions relative to output. Emission factors for each thermal installation i and each year t are defined as

$$\phi_{i,t} = \frac{E_{i,t}}{Q_{i,t}},$$

whereas $E_{i,t}$ denotes the annual CO_2 emissions and $Q_{i,t}$ the annual production.

We explain those emission factors by two types of variables: system-specific variables and installation-specific variables. The amount of renewable generation in the market and the residual demand left to all thermal installations in the system belong to the former category. These factors vary over time, but not over installation, while the installation variables vary over both dimensions, as, e.g., the commissioning year of the installation or its capacity.

We consider the annual residual demand RD_t, defined as the demand left to all thermal installations operating in the system, as a system-specific variable. Formally, we define it as

$$RD_t = (D_t - H_t - I_t) - R_t = D'_t - R_t,$$

whereas D_t denotes the annual electricity demand, R_t the amount of intermittent renewables in a year, H_t the annual net generation from hydro power,[5] and I_t the net imports, i.e., the imports minus exports. In this paper, we are mostly interested in the effect of an increase in R_t, hence we use only R_t and D'_t as explanatory variables. To enhance readability, we refer to D'_t as residual demand in the remainder of the paper although it describes only the demand minus hydro production and net imports.

Besides fixed effects for every installation, we also include several other installation-specific effects $X_{i,t} = (Y_{i,t}, \overline{Q}_{i,t}, G_{i,t})$ as control variables in our regressions. These

[5]We added electricity consumption for pumped hydro storage to the electricity generation from hydro plants. Hydro production from pumping amounted to only 1,711 GWh in 2014. Assuming an efficiency factor of 0.75, electricity consumption for pumped hydro storage represents only 0.8% of the total demand or 6.1% of PV and wind generation. Hence, we do not explicitly consider the effect of hydro storage.

are the commissioning year $Y_{i,t}$, capacity $\overline{Q}_{i,t}$, and the share of gas production $G_{i,t}$. The inclusion of the latter is motivated by the fact that gas plants have significantly lower emission factors than coal or oil plants. Thermal installations often consist of several production units. To account for that inter-installation variance, we put the unit-production weighted averages of the variables $Y_{i,t}$ and $G_{i,t}$. For example, if an installation consists of a gas and a coal generation unit and produces 876 GWh electricity with the former and 1,752 GWh with the latter technology, its gas share is equal to 1/3.

Similar to Bushnell and Wolfram (2005), we use fixed effects models and a log-log specification in our main specification.[6] We do not consider any dynamic effects since we operate with annual data. We estimate the following regression

$$\ln(\phi_{i,t}) = \beta_1 \ln(D'_t) + \beta_2 \ln(R_t) + \beta_3 X_{i,t} + \epsilon_{i,t}, \tag{1}$$

whereas the error term $\epsilon_{i,t}$ in (1) can be broken down into

$$\epsilon_{i,t} = \mu_i + \nu_{i,t},$$

where μ_i denotes the unobservable installation-specific fixed effect and $\nu_{i,t}$ the independent and identically distributed remainder error term, i.e., $\nu_{i,t} \sim \text{IID}(0, \sigma^2_{\nu_{i,t}})$. In our case the installation specific effects capture variables as technology, efficiency, and the like. Explanatory variables are assumed to be independent of $\nu_{i,t}, \forall i, t$.

We are mostly concerned about the size and the statistical significance of β_2 the coefficient of $\ln(R_t)$ in (1). Its interpretation is that a 1% increase in renewables increases the average installations' emission factor by β_2 percent. If it were zero, the second order effect of renewables on thermal plants emissions will be absent, or put differently, more intermittent renewables will not increase the inefficiency of the average plant.

We argue that all our explanatory variables are exogenous. Annual electricity consumption mostly depends on macroeconomic factors; net imports depend on market conditions in neighboring countries relative to the own country; and the production from hydroelectric plants depends on weather. The exact amount of renewable penetration also depends on weather conditions while the amount of installed renewable capacity mostly depends on subsidies which are politically decided.

[6] We use $X_{i,t} = (Y_{i,t}, \overline{Q}_{i,t}, G_{i,t})$ instead of $\ln(X_{i,t})$ since the gas share $G_{i,t}$ includes values of zero where the logarithm to the base of e is not defined. The qualitative findings of our study remain the same if we used $\ln(Y_{i,t})$ and $\ln(\overline{Q}_{i,t})$ instead of $Y_{i,t}$ and $\overline{Q}_{i,t}$.

3 Data and descriptive statistics

Italy is the geographical focus of this study for two reasons. First, because of the considerable increase of generation from wind and PV in the last few years and second, because of the excellent data availability for this market. Both factors qualify Italy for an excellent study case.

In order to identify the increased inefficiency of thermal installations caused by additional renewables in the system, we combine data-sets from five different sources: (i) accepted electricity market offers and bids at generation unit level published by the Italian electricity market operator (GME)[7], (ii) verified total emissions at installation level provided by the European Transaction Log (EUTL), (iii) data on renewable production and electricity consumption from the Italian transmission system operator (TERNA)[8], (iv) additional data on Italian power generators obtained from an Italian consulting company (REF-E)[9], and (v) data on imports and exports provided by the European Network of Transmission System Operators for Electricity (ENTSO-E).[10] Our data spans from 2005 to 2014.

3.1 Italian electricity market

The Italian electricity spot market is organized in a sequential manner, with a day-ahead market, five intra-day markets, and ancillary service markets. The day-ahead market is the most important one in terms of volume transactions. It started operation in 2004, but active demand bids entered the market in 2005. In the day-ahead market, generators and suppliers submit their supply and demand bids for each of the 24 hours of the next day. The day-ahead market price is determined in a single price, closed bid auction for every hour of the following day (see, e.g., Bigerna and Bollino, 2014, for a more detailed description of the market). In the presence of congestion in the electricity grid, the market is split into up to six different market zones (see Figure 1) with different prices. However, according to Bigerna et al. (2015, 2016); Sapio (2015) this is mainly an issue between Sicily and the mainland.

After the clearing of the day-ahead market, participants have the chance to re-balance their bids on the intra-day markets. In the last instance – in and near real

[7] We include accepted offers on the day-ahead spot market, as well as accepted net offers on intra-day and ancillary service markets.

[8] See http://www.terna.it.

[9] See http://www.ref-e.com.

[10] See https://www.entsoe.eu.

time – the transmission system operator TERNA acts as a counterpart to ensure that demand equals supply. Those interventions are necessary to guarantee system security and they are organized in the ancillary service markets.[11]

In order to derive the total production schedules of the generators, we add the net positions of the intra-day markets and ancillary service markets to the day-ahead market offers. The market bids also include bilateral trades hence it is possible to derive a very detailed production profile. This is confirmed when comparing the aggregated manually derived production to the total net production reported by TERNA over the years 2005 to 2014, which is around 95%. Hence, we conclude that the derived production serves as a valid proxy for actual production.

Figure 2 shows the Italian power production mix and its transition. Most production stems from thermal generation, whereas most of which comes from gas turbines. While thermal production shares have been around 80% between 2005 and 2008, they have decreased drastically thereafter due to a demand shock (economic crisis) and the large deployment of wind and PV. In 2014, thermal plants accounted for only 61% of Italy's total electricity production.

3.2 EU ETS

The European Union Emissions Trading System (EU ETS) is the largest cap-and-trade program in the world. The system was introduced in 2005 and is the main pillar of the EU climate policy. The EU ETS includes 31 countries (the 28 EU member states plus Norway, Iceland, and Liechtenstein) and more than 15,000 installations from the major industrial sectors. Specifically for the power sector, it includes all generating installations with a net heat excess of 20 MW. The definition of an installation in the EU ETS does not correspond to the definition of a generation unit in the power market and, in general, one installation in the EU ETS may include different generation units.

The EU ETS is a classic textbook cap-and-trade scheme. An annual cap on the total GHG emissions for the regulated sector is defined. An equivalent number of allowances are issued and distributed partially by auctioning and partially for free to the regulated installations. Allowances can be traded freely by installations and any other market participant, which leads to the formation of a uniform price for reducing a tonne of GHG emissions. Each installation must monitor their emissions and report them to the competent national authority. Each national authority verifies the information and

[11] For further details on the sequence of clearing, we refer to https://www.mercatoelettrico.org/En/Mercati/MercatoElettrico/MPE.aspx.

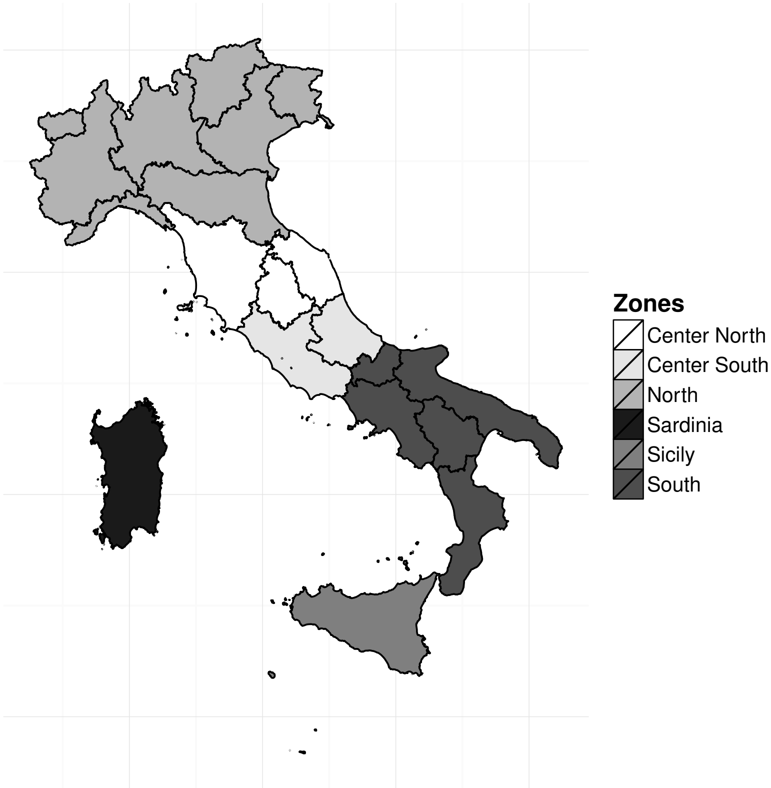


Figure 1: Italian market zones in 2014.

reports it to the European Commission that stores it in a central registry called the European Union Transaction Log (EUTL), which is publicly available.[12]

3.3 Data matching

We are able to derive hourly production schedules for each generating unit participating in the Italian electricity market. Data on CO_2 emissions from the EU ETS, however, is available only in annual resolutions and at installation level. A power installation defined by the EU ETS usually comprises more than one generation unit. Using the REF-E generator database, which includes technical information on most Italian power plants, we are able to match the spot market production data with the EU ETS emission data, and identify annual generation for almost all Italian EU ETS power

[12]The EUTL is available here http://ec.europa.eu/environment/ets/.

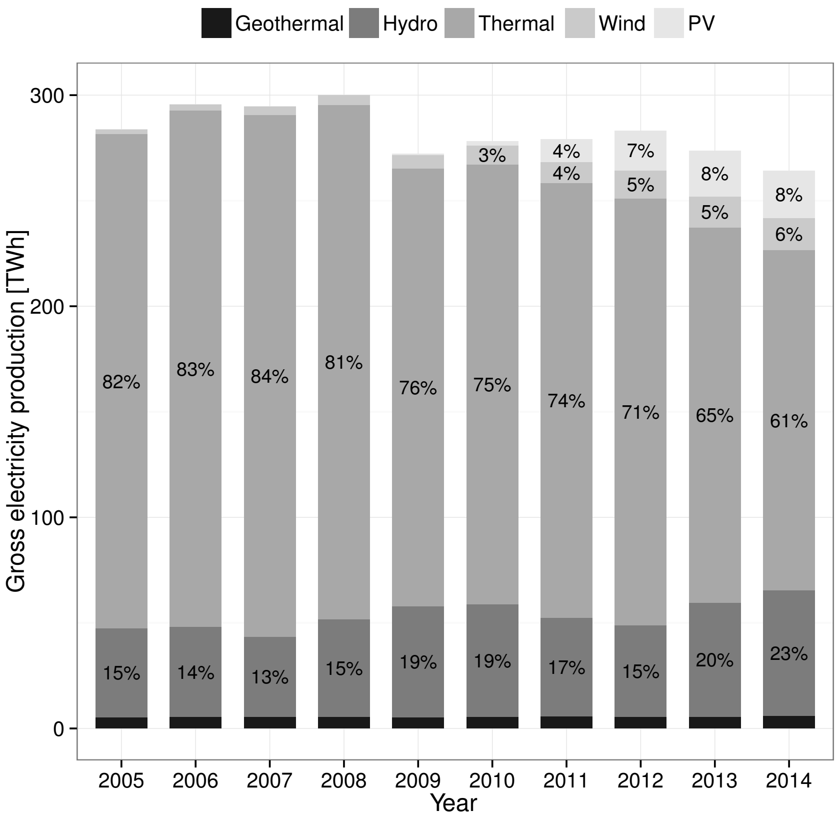


Figure 2: Italian yearly gross electricity production mix. Source: TERNA.

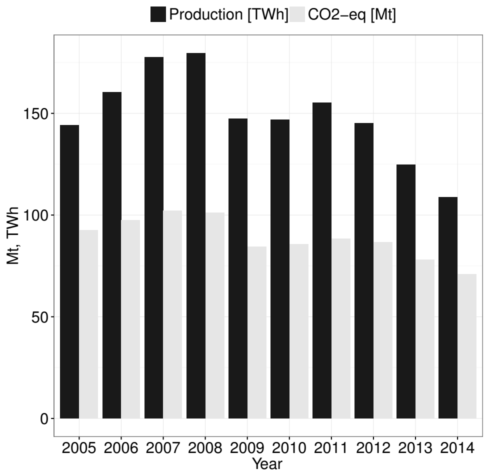
installations.[13] We managed to match 98 EU ETS installations, which represent 76% of the Italian gross thermal generation (excluding auto-production and geothermal production)[14] between the years 2005 and 2014.

According to the EIA, the average US CO_2 emission factors for natural gas plants were around 0.55 tons per MWh in 2013 and for bituminous coal around 0.94.[15] To avoid biased results and to hedge against data mismatch, we exclude installations with annual emission factors larger than two in one of the ten years of observations.

[13]The European Commission (EC) provides data on emissions at installation level including the 4 digit NACE code for the years 2005 until 2012, see `http://ec.europa.eu/clima/policies/ets/cap/leakage/studies_en.htm`. NACE Rev. 2 code 35.11 stands for "Production of electricity." We used this list as a starting point to match the data and manually applied the remainder.

[14]Data provided by TERNA.

[15]EIA reports pounds of CO_2 per kWh for bituminous coal equal to 2.07 and for natural gas equal to 1.21. Data are calculated using the average heat rates for US steam-electric generators in 2013. See `http://www.eia.gov/tools/faqs/faq.cfm?id=74&t=11`.



(a)

(b)

Figure 3: Panel (a): Aggregated production/emissions of the thermal plants in our sample. Panel (b): Aggregated emissions relative to aggregated production.

Disproportionately high emission factors are often in plants that are in operation only for a few hours in a year. In the most extreme case, the emissions produced by switching on a unit whose spot market offer is accepted only for one single hour in a year exceeds the emissions produced by generating electricity for this particular hour.

By restricting the emission factor, our remaining sample still covers 93 Italian EU ETS power generation installations, which represent 73% of Italy's total net thermal production between 2005 and 2014. In comparison to the total of 98 matched installations, we still cover 96% of the emissions. The 93 installations contain 219 generation units, so on average an installation consists of about two generating units.

3.4 Descriptive statistics

Figure 3, Panel a, shows aggregated yearly production and emissions of the installations in our sample. The production pattern is similar to that of all Italian thermal plants as depicted in Figure 2. Emissions are coupled with production – the more production the higher the emissions. However, the emissions relative to output vary considerably over time, as can be seen in Figure 3 (b). While the emission factor decreased between 2005 to 2008, it has increased thereafter and quite impressively after 2011 – the time when intermittent renewables started playing an even more important role in the power mix.

Variable	Abbr.	Mean	SD	Min	Max	Unit
Production	Q	1,932,273	2,357,708	71	16,700,000	MWh
Emissions	E	1,151,493	1,854,618	65	15,300,000	tCO_2
Emission factor	ϕ	0.65	0.28	0.36	1.66	Ratio
Renewables	R	15,959,000	14,481,743	2,347,000	37,484,000	MWh
Residual demand	D'	221,161,648	17,035,207	189,956,525	242,104,675	MWh
Commissioning year	Y	1995	15	1954	2013	Year
Capacity	$\overline{Q}$	613	525	17	2,640	MW
Gas share	G	0.71	0.45	0	1	Ratio

Table 1: Descriptive statistics.

In Table 1, we show the descriptive statistics of variables used in our regressions.

4 Results

4.1 Baseline regression

In order to estimate the average effect of additional electricity generation by intermittent renewables sources on thermal plants' emission factors, we run several specifications of the regression model stated in (1). We always use robust standard errors clustered by installation in order to allow for heteroskedasticity and correlation over time for a given installation.

4.1.1 All installations

We report the regression results including all installations in column 1 of Table 2. An increase of 1% intermittent renewables in the system leads to a 0.03% higher emission factor on average. All other factors negatively affect the emission factor. The absolute value of β_1 – the coefficient of $\ln(D')$ – is larger than that of renewables, which can be explained by the different levels of the two variables. Thermal installations benefit far more from a percentage increase of D' than suffer from a percentage decrease in R since current production of wind and PV is only about one-tenth of the maximum residual demand.

Younger plants have lower emission factors, i.e., a one-year increase in the commissioning year leads to a decrease of the emission factor by about one percent. The capacity variable is statistically insignificant while the gas share coefficient is significant. Most gas installations consist only of a single generation unit or are operating

	(all)	(base)	(peak)	(old)	(zonal)
$\ln(D')$	-0.121^{*}	-0.165^{***}	-0.123	-0.204^{**}	
	(0.053)	(0.037)	(0.107)	(0.067)	
$\ln(R)$	0.026^{***}	0.013^{***}	0.041^{***}	0.038^{**}	
	(0.006)	(0.003)	(0.010)	(0.011)	
Y	-0.013^{***}	-0.013^{***}	-0.006	-0.018^{***}	-0.012^{***}
	(0.003)	(0.003)	(0.010)	(0.003)	(0.002)
$\overline{Q}$	-0.000	0.000	-0.000		-0.000
	(0.000)	(0.000)	(0.000)		(0.000)
G	-0.312^{**}	-0.311^{*}	0.095		-0.363^{**}
	(0.102)	(0.132)	(0.710)		(0.107)
$\ln(zD')$					-0.096^{*}
					(0.046)
$\ln(zR)$					0.013^{***}
					(0.003)
R^2 within/between	0.40/0.66	0.58/0.86	0.25/0.03	0.27/0.48	0.40/0.67
Observations	771	398	373	230	771
Installations	93	51	47	23	93

Notes: Robust standard errors clustered by installation reported in parentheses. Asterisks indicate statistical signicance at 5% (*), 1% (**), and 0.1% (***) levels.

Table 2: The effect of renewables on emission factors.

together with other gas generating units, hence the gas share mostly acts as an indicator variable.

The R^2, and thereby the fraction of explained variation, is 40% between installations and 66% within installations. The values are reasonable and limit the possibility of wrongly estimated coefficients due to omitted variables.

4.1.2 Examining installation heterogeneity

The fixed effects model captures firm heterogeneity by including an indicator variable for every installation. Thus, the intercept is allowed to change for every installation. The installation's slopes, however, are homogenous which means that the respective coefficients reflect only the average effect of, e.g., additional renewable infeed. Such a model does not fully account for the peculiarities of power systems. Cheap renewables first displace expensive peak-load generation and their emissions. Given that installed renewable capacity is low to moderate, base-load plants are affected only in situations of low demand and high renewable production. In terms of flexibility, i.e., load-cycling, peak-load plants outperform base-load plants. Hence, adjusting the load of a peak-load generation unit is much more efficient in terms of cost and emissions. Consequently, there are two contrary effects at work: peak-load installations are more frequently affected but the impact on emission factors is smaller compared to base-load installations which are affected less frequently but the impact is higher.

Our first strategy to account for the difference in slope heterogeneity is to split the sample into base-load and peak-load installations. We classify as base-load installations the installations consisting of more than 50% of coal generating units or producing more than half of their total annual production with combined cycle units. The remaining installations we define as peak-load installations. As a second strategy, we run a random coefficient model whose results are presented in Section 4.3.1.

Column 2 in Table 2 reports the results including only base-load installations. It turns out that the coefficient of renewables is lower compared to the baseline regression (column 1). When reducing the sample to peak-load installations only, we observe a larger effect. Hence, we find evidence that, at current levels of intermittent renewables in the system, the peak-load installations' emission factors are affected more (column 3) than those of base-load installations.

4.1.3 The role of investment

Another source of heterogeneity are installations that have built up new capacity in comparison to installations which have not done so. In order to identify the role of investment in newer generating units, we look at installations which have been active for the whole period and did not change capacity during that time. New capacity build-up is generally more efficient and, possibly, the response to a changed market environment. By including only installations which technically have not changed, we are able to isolate the short-run effect of renewables on emission factors. The results – stated in column 4 of Table 2 – show that the effect of additional renewables on emission factors is larger (0.04%) compared to that of the baseline scenario (0.03%) where we include all installations. Hence, relative emissions from installations that have not been adapted in the ten years show a higher response to increased penetration from renewables.

Figure 4 shows the installed capacity of the installations in our sample. There has been considerable investment in gas generation units from 2005 to 2012. Oil units almost completely disappeared while the capacity of coal has been slightly increased from 2009 to 2012 and was about the same in 2014 as in 2005.

The massive investment in gas generation units possibly led to the drop in the overall emission factor in 2008 and 2011, as can be seen in Figure 3(b).[16]

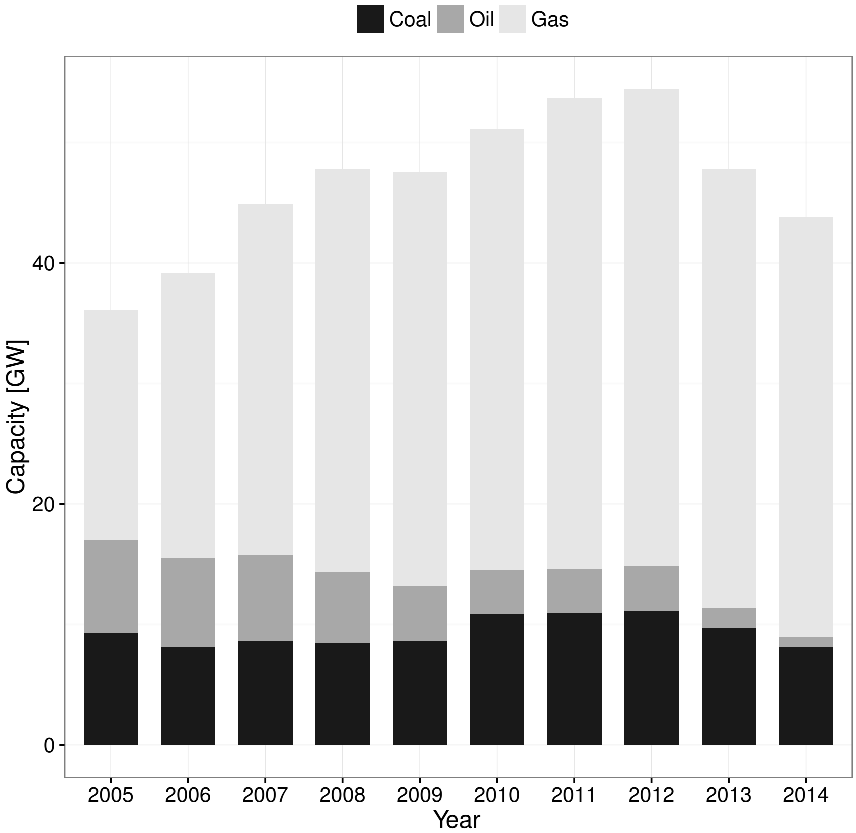


Figure 4: Installed capacity.

4.1.4 Market splitting

In case of physical congestion, Italy's electricity market can be divided into six different market zones. In order to account for possible market splitting, we replace cross-country residual demand and generation from intermittent renewable sources by their zonal values. We denote the former by zD' and the latter by zR. The positive effect of additional renewable generation on the emission factor is still statistically significant

[16]According to TERNA, the amount of combined cycle gas capacity has roughly doubled between 2004 and 2014, see "Impianti di generazione" under `http://www.terna.it/it-it/sistemaelettrico/statisticheeprevisioni/datistatistici.aspx`.

	(all)	(base)	(peak)	(old)	(zonal)
$\ln(D')$	1.185**	1.869***	0.694	1.282	
	(0.400)	(0.533)	(0.620)	(0.708)	
$\ln(R')$	−0.427***	−0.310***	−0.536***	−0.264**	
	(0.054)	(0.065)	(0.083)	(0.076)	
Y	0.013	−0.000	0.022	0.075**	−0.005
	(0.011)	(0.037)	(0.037)	(0.026)	(0.012)
$\overline{Q}$	0.001**	0.000	0.002***		0.001**
	(0.000)	(0.000)	(0.001)		(0.000)
G	−0.791	−0.569	1.363		−0.040
	(0.882)	(1.623)	(1.561)		(1.010)
$\ln(zD')$					0.962*
					(0.439)
$\ln(zR)$					−0.179***
					(0.027)
R^2 within/between	0.42/0.28	0.45/0.41	0.46/0.27	0.31/0.03	0.34/0.18
Observations	771	398	373	230	771
Installations	93	51	47	23	93

Notes: Robust standard errors clustered by installation reported in parentheses. Asterisks indicate statistical signicance at 5% (*), 1% (**), and 0.1% (***) levels.

Table 3: The effect of renewables on verified emissions.

albeit at a slightly lower level (see column 5 in Table 2). According to Bigerna et al. (2015, 2016); Sapio (2015) inter-market congestion is mainly an issue between Sicily and the mainland, which weakens the importance of this specification. Hence, in the remainder of the paper we mainly concentrate on the other cases.

4.2 Magnitude of the effect

An important issue is the magnitude of the increased inefficiency caused by renewables. More precisely, the share of the increased inefficiency in comparison to the offset emissions. Therefore, we estimate also the first-order effect of renewables on the emissions, i.e., $\ln(E_{i,t})$. As explanatory variables, we use the same as specified in (1). Table 3 shows the estimates for the five versions as we had it before with the emission factors.

The coefficients of $\ln(R)$ are negative and statistically significant in all specifications. Their values range between -0.26 and -0.54, i.e., a one percent increase in intermittent renewables leads to a reduction of emissions between 0.26 and 0.54 per-

	(all)	(base)	(peak)	(old)	(zonal)
β_2	0.03	0.01	0.04	0.04	0.01
β'_2	-0.43	-0.31	-0.54	-0.26	-0.18
$\beta'_2/(\beta'_2 - \beta_2)$	94%	96%	93%	87%	93%

Table 4: Percent of expected emissions reduction.

cent. The coefficient of residual demand is positive although not statistically significant in the sample restricted to peak-load installations and non-modified installations. The R^2 are reasonable in all specifications.

To quantify the magnitude of the second order effect, we rearrange the marginal effect of renewables on emission factors from (1) as

$$\beta_2 = \frac{\mathrm{d}\left(\ln\left(\phi_{i,t}\right)\right)}{\mathrm{d}\ln\left(R_t\right)} = \frac{\mathrm{d}\left(\ln\left(E_{i,t}/Q_{i,t}\right)\right)}{\mathrm{d}\ln\left(R_t\right)} = \frac{\mathrm{d}\left(\ln\left(E_{i,t}\right) - \ln\left(Q_{i,t}\right)\right)}{\mathrm{d}\ln\left(R_t\right)} = \frac{\mathrm{d}\ln\left(E_{i,t}\right)}{\mathrm{d}\ln\left(R_t\right)} - \frac{\mathrm{d}\ln\left(Q_{i,t}\right)}{\mathrm{d}\ln\left(R_t\right)}. \tag{2}$$

Furthermore, we denote the estimate of the marginal effect of renewables on the installations' emissions, i.e., $(\mathrm{d}\ln(E_{i,t}))/(\mathrm{d}\ln(R_t)) = \beta'_2$. Substituting β'_2 in (2) yields

$$\left(\mathrm{d}\ln\left(Q_{i,t}\right)\right) / \left(\mathrm{d}\ln\left(R_t\right)\right) = \beta'_2 - \beta_2,$$

which is the effect as if renewables had displaced all thermal capacity without causing additional inefficiencies. Hence, the percentage value of expected emissions reductions can be written as $\beta'_2/(\beta'_2 - \beta_2)$. In Table 4, we show the calculations for each of the five models. Including all installations (column 1), we see that the average installation achieves around 94% of the expected reductions accounting for the additional inefficiency caused by renewables. The percentage share is lower (87%) for installations that have not seen investment over the ten years.

Our estimates are less pessimistic than that of Katzenstein and Apt (2009) who find that CO_2 emissions achieve only around 80% of the expected emissions reductions. A possible explanation for this gap is that we apply an electricity market perspective while Katzenstein and Apt (2009) are focusing only on two types of natural gas generators. As pointed out by Cullen (2013), in an electricity market the reduction in production induced by intermittent renewables may be shared among many installations which may incur smaller changes in emission due to ramping and reduced efficiency.

4.3 Robustness checks

Both, a Hausman test and a test for over-identification favor a random effects model instead of a fixed effects model. However, the fixed effect model, which literally allows for a different intercept of each installation seems to be more plausible. Furthermore, the coefficients of interest in both models are almost the same (see Tables 5 and 6 in the Appendix) and there is no difference when calculating the percent of expected emissions reductions as in Table 4. We use robust standard errors clustered by installation in all regressions to allow for heteroskedasticity and correlation over time for a given installation. A Pesaran cross-sectional dependence test on the balanced panel, i.e., only taking into account installations which have been active over the whole sample period, cannot be rejected. To fix this issue, we run a second specification including time fixed effects (see Tables 7 and 8 in the Appendix) instead of $\ln(D')$. The coefficients of $\ln(R)$ in the regression where we used emission factors as dependent variable are slightly larger in all specifications than they were before (see Table 8). However, calculating the percent of expected emissions reductions as in Table 4 yields similar results. These exercises demonstrate that our derived results are robust to different methods of estimating the effect of renewables on emissions.

4.3.1 Random coefficient model

In order to account for heterogeneous slopes, we also estimate a random coefficient model. Table 9 shows the result of regressing emissions and emission factors on renewables, demand, and the commissioning year. The average values of the relevant coefficients – renewables and residual demand – are in the range of the fixed effect model, and so is the expected emissions reduction. Figure 5 shows a histogram of the individual slopes for each installation.

4.3.2 Alternative weights

In Section 2, we defined installation-specific variables as the production weighted variables of each generation unit. As a robustness check, we substituted production weights for capacity weights. The coefficients of renewables are slightly lower in the regression where we use emission factors as a dependent variable. All coefficients are statistically significant except the coefficient of renewables in the fixed effect estimation restricting to base load installations. However, the expected reductions are in the same range as in the original specification.

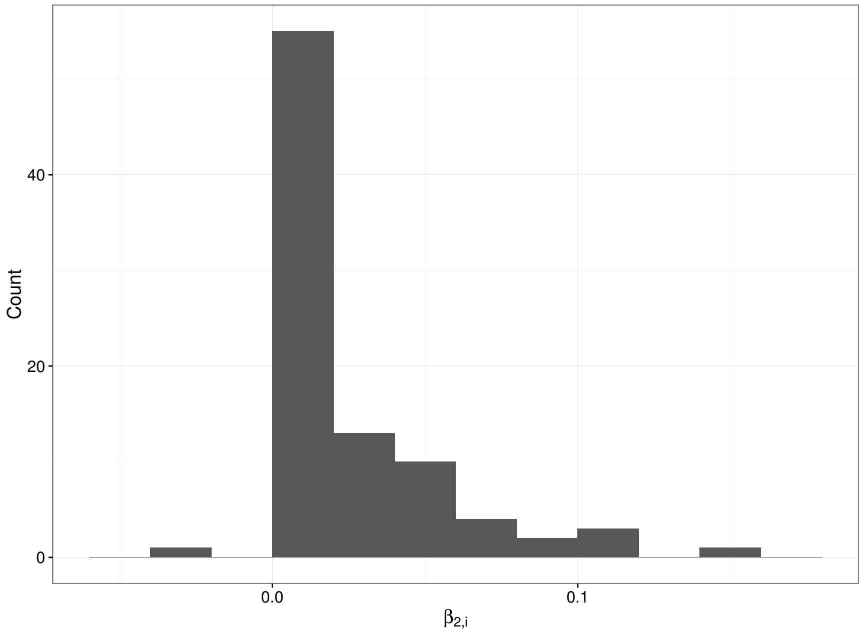


Figure 5: Histogram showing the coefficients of $\ln(R)$.

5 Conclusion

In this paper, we show that electricity generation from intermittent renewables has had a measurable positive effect on the efficiency of Italian thermal installations between 2005 and 2014. While the emissions of the average installation have been reduced, the emissions relative to output have increased. Our results show that intermittent renewables lessen the emission reduction by 6% for the average installation. At the current levels of PV and wind generation in the Italian power system (around 14% of annual gross electricity production in 2014), base-load installations are less affected than peak-load installations.

Our work shows that the impact of PV and wind on the efficiency of thermal installation is effectively a second order impact on emission reductions. However, it is not too small to be completely neglected either, especially in the future, when the increase in the penetration of renewables will affect much more base-load installations, which are less capable of coping with variable load-profiles. This effect can be mitigated by all the methods that can be used to mitigate the impact of intermittency: by storage, transmission lines, demand side management, and by improving the design of new thermal power plants.

The main limiting factor of our study is that emissions of European installations are currently monitored only on an annual basis. This forced us to do a yearly analysis despite having information on installation production at an hourly level. The second limitation is that we could not factor in the different effects of PV and wind on installation level emissions, due to the high correlation in the yearly observations.

Our analysis can be further developed in several directions. In addition to trying to disentangle the effect of PV and wind on emissions, an important extension would be to evaluate how increased inefficiency affects the cost of generation, and thus the evolution of the power market.

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A Appendix

	(all)	(base)	(peak)	(old)	(zonal)
$\ln(D')$	1.035^{**}	1.698^{***}	0.587	1.294	
	(0.431)	(0.477)	(0.720)	(0.750)	
$\ln(R')$	-0.423^{***}	-0.310^{***}	-0.534^{***}	-0.260^{***}	
	(0.035)	(0.038)	(0.057)	(0.045)	
Y	0.013	0.017	0.028	0.058^{*}	0.001
	(0.011)	(0.037)	(0.037)	(0.026)	(0.012)
$\overline{Q}$	0.002^{***}	0.001^{***}	0.002^{***}	0.002^{***}	0.002^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
G	-0.423	-1.423^{***}	0.123	-1.411	-0.181
	(0.882)	(0.414)	(0.579)	(0.934)	(0.408)
$\ln(zD')$					0.233
					(0.194)
$\ln(zR)$					-0.193^{***}
					(0.015)
R^2 within/between	0.42/0.37	0.44/0.61	0.46/0.35	0.30/0.49	0.33/0.37
Observations	771	398	373	230	771
Installations	93	51	47	23	93

Notes: Robust standard errors clustered by installation reported in parentheses. Asterisks indicate statistical signicance at 5% (*), 1% (**), and 0.1% (***) levels.

Table 5: The effect of renewables on verified emissions (Random effects model).

	(all)	(base)	(peak)	(old)	(zonal)
$\ln(D')$	-0.125^{*}	-0.170^{***}	-0.139	-0.207	
	(0.056)	(0.032)	(0.112)	(0.124)	
$\ln(R)$	0.026^{***}	0.011^{***}	0.040^{***}	0.037^{***}	
	(0.004)	(0.002)	(0.008)	(0.008)	
Y	-0.012^{***}	-0.009^{***}	-0.008^{***}	-0.014^{***}	-0.011^{***}
	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)
$\overline{Q}$	-0.000^{***}	0.000	-0.000^{**}	-0.000	-0.000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
G	-0.394^{***}	-0.557^{***}	-0.352^{***}	-0.402^{***}	-0.405^{***}
	(0.054)	(0.064)	(0.081)	(0.118)	(0.053)
$\ln(zD')$					-0.063^{*}
					(0.027)
$\ln(zR)$					0.014^{***}
					(0.002)
R^2 within/between	0.40/0.67	0.58/0.90	0.25/0.44	0.27/0.63	0.40/0.68
Observations	771	398	373	230	771
Installations	93	51	47	23	93

Notes: Robust standard errors clustered by installation reported in parentheses. Asterisks indicate statistical signicance at 5% (*), 1% (**), and 0.1% (***) levels.

Table 6: The effect of renewables on emission factors (Random effects model).

	(all)	(base)	(peak)	(old)	(zonal)
$\ln(D')$					
$\ln(R)$	-0.506^{***}	-0.450^{***}	-0.528^{***}	-0.364^{***}	
	(0.061)	(0.080)	(0.090)	(0.095)	
Y	0.015	-0.001	0.027	0.070^{**}	0.018
	(0.011)	(0.037)	(0.039)	(0.022)	(0.013)
$\overline{Q}$	0.001^{**}	0.000	0.002^{***}		0.001^{**}
	(0.000)	(0.000)	(0.001)		(0.000)
G	-0.816	-0.457	1.830		-1.045
	(0.900)	(1.642)	(1.959)		(0.895)
$\ln(zD')$					-0.060
					(1.174)
$\ln(zR)$					0.076
					(0.077)
Time fixed effects	yes	yes	yes	yes	yes
R^2 within/between	0.43/0.30	0.45/0.38	0.47/0.23	0.32/0.03	0.43/0.27
Observations	771	398	373	230	771
Installations	93	51	47	23	93

Notes: Robust standard errors clustered by installation reported in parentheses. Asterisks indicate statistical signicance at 5% (*), 1% (**), and 0.1% (***) levels.

Table 7: The effect of renewables on verified emissions including time fixed effects.

	(all)	(base)	(peak)	(old)	(zonal)
$\ln(D')$					
$\ln(R)$	0.044^{***}	0.033^{***}	0.065^{***}	0.064^{**}	
	(0.009)	(0.004)	(0.016)	(0.015)	
Y	-0.013^{***}	-0.014^{***}	-0.006	-0.018^{***}	-0.013^{***}
	(0.003)	(0.003)	(0.010)	(0.002)	(0.002)
$\overline{Q}$	-0.000	0.000	-0.000		-0.000
	(0.000)	(0.000)	(0.000)		(0.000)
G	-0.310^{**}	-0.279^{*}	0.105		-0.325^{**}
	(0.100)	(0.132)	(0.637)		(0.104)
$\ln(zD')$					-0.035
					(0.123)
$\ln(zR)$					0.004
					(0.007)
Time fixed effects	yes	yes	yes	yes	yes
R^2 within/between	0.42/0.66	0.65/0.85	0.28/0.03	0.29/0.48	0.43/0.67
Observations	771	398	373	230	771
Installations	93	51	47	23	93

Notes: Robust standard errors clustered by installation reported in parentheses. Asterisks indicate statistical signicance at 5% (*), 1% (**), and 0.1% (***) levels.

Table 8: The effect of renewables on emission factors including time fixed effects.

Dependent variable	(all) $\ln(E)$	(all) $\ln(\phi)$
$\ln(D')$	2.151^{***}	-0.057
	(0.341)	(0.046)
$\ln(R)$	-0.405^{***}	0.024^{***}
	(0.049)	(0.004)
Y	-0.011^{***}	0.000
	(0.003)	(0.000)
Observations	762	762
Installations	89	89

Notes: Bootstrapped standard errors in parentheses. Asterisks indicate statistical signicance at 5% (*), 1% (**), and 0.1% (***) levels.

Table 9: The effect of renewables on emission factors applying a random coefficient model without constant.

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